Expertise as Sensorimotor Tuning

Perceptual Navigation Patterns Mark Representational Competence in Science

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Abstract:	Representational competence in science is the ability to generate external representations (e.g. equations, graphs) of real-world phenomena, transform between these representations, and use them in an integrated fashion. Difficulties in achieving representational competence are often considered central to difficulties in learning science. Representational competence is indicative of domain expertise and is characterised by distinct problem-solving strategies. Eye-tracking studies have consistently demonstrated that experts employ unique perceptual attention (e.g. gaze-fixation) patterns while solving problems that involve different external representations. Here we present a different strand of evidence, indicating that perceptual navigation patterns (eye-movements) mark representational competence in science, in more specific ways than attention. Gaze behaviours of chemistry professors (experts) and undergraduate students (novices) were tracked as they individually performed a multi-representational categorisation task and a chemical equation-balancing task. The following three-step analysis was performed on these data: (i) First we independently calibrated the levels of representational competence of our participants through their performance in the categorisation task. (ii) Then, we compared these competence-levels with the participants' perceptual patterns (gaze behaviour) exhibited during the categorisation task. (iii) Finally, we analysed whether the identified perceptual patterns were specific to representational competence, or more general, through the results of the equation-balancing task. Our analysis of perceptual navigation (eye movements) provided further support to previous findings showing gaze behaviour differences between experts and novices. Going further, our analysis indicated that experts deploy distinct eye-movement patterns, but specifically during representational competence-related problems. This suggests that representational competence is an embodied skill that fundamentally changes the tuning of the perceptual system, as argued by recent 'field' theories of cognition.

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Running title

Perceptual navigation marks expertise in science

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Expertise as Sensorimotor Tuning: Perceptual Navigation Patterns Mark Representational Competence in Science

Abstract

Representational competence in science is the ability to generate external representations (e.g. equations, graphs) of real-world phenomena, transform between these representations, and use them in an integrated fashion. Difficulties in achieving representational competence are often considered central to difficulties in learning science. Representational competence is indicative of domain expertise and is characterised by distinct problem-solving strategies. Eye-tracking studies have consistently demonstrated that experts employ unique perceptual *attention* (e.g. gaze-fixation) patterns while solving problems that involve different external representations. Here we present a different strand of evidence, indicating that perceptual *navigation* patterns (eye-movements) mark representational competence in science, in more specific ways than attention.

Gaze behaviours of chemistry professors (experts) and undergraduate students (novices) were tracked as they individually performed a multi-representational categorisation task and a chemical equation-balancing task. The following three-step analysis was performed on these data: (i) First we independently calibrated the levels of representational competence of our participants through their performance in the categorisation task. (ii) Then, we compared these competence-levels with the participants' perceptual patterns (gaze behaviour) exhibited during the categorisation task. (iii) Finally, we analysed whether the identified perceptual patterns were specific to representational competence, or more general, through the results of the equation-balancing task. Our analysis of perceptual navigation (eye movements) provided further support to previous findings showing gaze behaviour differences between experts and novices. Going further, our analysis indicated that experts deploy distinct eye-movement patterns, but specifically during representational competence-related problems. This suggests that representational competence is an embodied skill that fundamentally changes the tuning of the perceptual system, as argued by recent ‘field’ theories of cognition.

Keywords: Representational competence; Multiple representations; Perceptual learning; Eye tracking; Embodied cognition; Sensorimotor.

Introduction

Learning and practising science involves studying complex systems, entities and phenomena that often cannot be directly perceived or interacted with (e.g. DNA, chemical reactions). External representations[1] (e.g. diagrams, equations, simulated models; for better readability, simply referred to as ‘representations’ hereafter) help us access, interact with, imagine, and reason about these systems, at different spatio-temporal granularities. Gaining expertise over representations is thus critical to science education (Yore & Hand, 2010). The ability to generate and use representations in a domain in an integrated fashion, and perform transformations on the representations, is termed as representational competence (Kozma & Russell, 1997 & 2005).

Representational competence is indicative of domain expertise. Many learning difficulties students face in science are attributable to problems in achieving representational competence (Johnstone, 1991 & 2000; Stieff et al., 2015). Domain experts in science significantly differ from novices in their abilities to understand individual representations and integrate different representations, and the capacity to use and generate different representations for conceptual

[1]For better readability, we use the term ‘representation’ instead of ‘external representation’ hereafter. Our usage of this term is restricted to mean *external* representation (emphasising its physically external relationship to the neural mind), unless stated otherwise.

understanding, discovery and problem solving (various sub-skills involved in representational competence; Chi et al., 1981; Kohl & Finkelstein, 2008).

Behavioural evidence, especially on visual attention and perception with respect to 2- and 3-dimensional representations, demonstrates how experts differ from novices while solving problems related to representational competence. For instance, while observing animations of molecular mechanics during problem solving, novices tend to fixate their vision more on (i.e. attend more to) familiar visuospatial representations (e.g. molecular models), compared to less-known symbolic representations such as equations (Stieff et al., 2011). Novices also spend more time attending to parts of a diagram where problem-relevant information is scarce or absent, as compared to experts who tend to fixate longer on the ‘perceptually salient’, relevant, and information-rich areas in diagrams (Madsen et al., 2012).

A wider meta-analysis across multiple domains, including the natural sciences, medicine, computer science, and chess, has shown that experts visit task-relevant areas in and across representations more frequently than novices, and spend more time there than on task-redundant areas (NRC, 2000). In addition, experts also exhibit longer saccades (rapid involuntary eye-movements between successive fixations) and shorter times to first fixation, on relevant information in representations (Gegenfurtner et al., 2011). Further, the distribution of fixation-duration (i.e. time spent looking) across different representations, and different areas in a representation, have been considered good predictors of problem-solving performance (e.g. Chen et al., 2014).

Experts and novices also differ in the way they navigate (i.e. move their eyes over) representations – usually measured in terms of gaze transitions (eye-movements between two different representations, or two areas within the same representation). For instance, students with low prior knowledge (novices) are known to make more gaze transitions on average than expert students (Cook et al., 2008; Kohl and Finkelstein, 2008), because novices need to make more attempts to map the different features between several representations, as they are less aware of the 'subtleties of representations and the conventions for interpreting them'.

Classical information processing theories of the mind account for these differences as 'visual/perceptual strategies' that help experts reduce cognitive load when extracting, storing and processing, and mapping task-relevant information from different features of representations (Chi et al., 1981; Cook et al., 2008; Johnstone, 1982 & 1991; Ozogul et al., 2012; Schnotz, 2002).

However, expertise or representational competence is characterised by not only the efficiency in seeing the different features of representations or mapping between them, but also the merging of perception of representations with an imagination of the dynamics of the represented phenomenon (e.g. motion; Schnepp & Nemirovsky, 2001), and building dynamic mental models of that phenomena through an *integration* of the representations (Gilbert, 2005; Kozma & Russell, 2005; Levy & Wilensky, 2009).

Recent research has suggested strong links between perceptual and cognitive processes, and perception and mental models of abstract concepts (Bottini & Doeller, 2020; Landy et al., 2014; Markauskaite, Kelly & Jacobson, 2020; Rau, 2015). It is conjectured that the so-called 'visual strategies' experts 'use' to simulate and imagine the individual and collective behaviours of components of the phenomena, and the effects of various parameter changes on such behaviours (Hegarty, 2004; Levy & Wilensky, 2009; Schnotz & Bannert, 2003), could stem from their detailed mental models. Such detailed mental models are considered to 'run' on perception and action systems indicating that the difference in the perceptual behaviours between experts and novices is sensorimotor in nature (Chandrasekharan, 2014; Nersessian, 2008), and cannot be considered simply as cognitive strategies.

Research on perceptual learning provides empirical support for this conjecture, primarily in the context of mathematics. Perceptual learning is characterised by changes in the process of information pick-up, and changes in the perceptual-cognitive system (as well as mental models) of a learner as a result of visuospatial routines (perceptual manipulations theory; Landy et al., 2014), training and experience (Goldstone, 1998; Kellman & Garrigan, 2009). For instance, Kellman and colleagues (2010) studied perceptual learning in terms of how transforming the structure of an algebraic equation affects the difficulty level as well as response times to solve that equation. They showed that people with diverse experiences with different forms of equations find some forms of equations more relevant than others. Moreover, this relevance is established almost instantly after perceiving the problem. Qualitative differences between experts and novices, in their experiences with symbolic structures involved in a problem, are known to cause qualitatively different perceptual behaviour (Braithwaite et al., 2016; Kellman et al., 2010; Landy & Goldstone, 2007; Matuk & Uttal, 2020; Rivera & Garrigan, 2016).

Theoretical background and motivation

Extended and embodied cognition models of the mind (e.g. Clark & Chalmers, 1998; Glenberg et al., 2011; Hutchins, 2014; Körner, Topolinsky & Strack, 2015) have suggested that scientific reasoning (in the context of discovery; Chandrasekharan, 2014) and imagination (in the context of learning; Authors, 2017), emerge from an action-based incorporation and sensorimotor simulation of external structures (such as representations) by the brain. For instance, brain imaging studies of arithmetic operations done mentally, across people who learned to do difficult arithmetic sums using the abacus, and a control group who learned arithmetic using paper/pencil, show that the action and visual areas are activated more for the abacus group. This result indicates that participants in the abacus group have internalised a 'mental abacus'. The abacus case demonstrates that the brain 'incorporates' the representation with which 'it' interacts (e.g. abacus, paper/pencil) into the action schema of arithmetic (Author, 2020). Extending this finding, even highly abstract symbolic external structures (e.g. algebraic expressions) and an agent's sensorimotor interactions with them (e.g. arithmetic operations) have been shown to *constitute* their understanding of, and reasoning with, concepts related to those structures (Rahaman et al., 2017). Further, empirical work, specifically in the context of scientific representations, has suggested that the mind, during representational integration, is thought to constantly engage in: *unfreezing* – which involves simulating dynamic states of a representation in relation to the represented phenomena (Hegarty, 2004), and *freezing* – which involves isolating and imagining 'static' states of the representation(s) and represented phenomena (Authors, 2017). These unfreezing and freezing processes are facilitated by similar sensorimotor mechanisms that help us simulate (a sense of) movement from sketches and drawings, and infer complex physical relationships (e.g. velocity, momentum) from traces of past movements (e.g. tyre marks; Bub & Mason, 2012; Chandrasekharan, 2014).

In summary, while information processing views assume that a learner's actions (e.g. eye-movements) merely facilitate information extraction from representations, so that information-based mental models could be formed, 'field theories' (extended and embodied cognition) argue that mental models are *constituted* by interactive behaviours (e.g. eye-movements exhibited on the representations) as well as internal copies of the actions on the representations themselves (Landy et al., 2014). Sensorimotor mechanisms are thus critical to the fundamental cognitive processes (e.g. mental models) underlying representational integration (e.g. incorporation of representations, constitution). This theoretical position suggests that the development of representational integration ability could result in a fundamental reorganisation of the sensorimotor system, thus changing how learners access representations (e.g. perceptually) over time. In other words, distinct sensorimotor-level behavioural patterns (e.g. gaze) would mark representational competence and expertise (Author, 2020).

Our cross-sectional study (Salkind, 2006; Vandenbos, 2015) is theoretically motivated by this cognitive science perspective (Authors, 2017; Hutchins, 2014). The broad goal of this study was to examine whether possible links existed, between changes in the perceptual-sensorimotor system, and development of expertise in science (for a detailed account of the emergence of this conjecture, see Author, 2020). Our results present indicative evidence that there exists distinct eye-movement behaviour related to expertise. Though similar findings are reported in the existing literature on representational competence, the above theoretical framing of our study provides an integrated understanding of representational competence, as (sensorimotor-level) changes in experts' perception and action systems, emerging from their interaction with representations.

To operationalise the question of whether sensorimotor changes emerge from extensive interaction with representations, we:

- documented gaze-related perceptual[2] markers of representational competence in science, and
- examined whether these markers are activated and exhibited among experts only during representational competence-related problems.

[2]In the context of this paper, we use the term 'perceptual' in a limited sense to refer only to visual perception.

To do this, we tracked the gaze behaviour of chemistry professors (experts) and undergraduate students (novices) as they individually performed a representational-categorisation task (Kozma & Russell, 1997) and a chemical equation-balancing task (Yarroch, 1985). The obtained data were then analysed in three steps:

1. calibrating participants' representational competence-levels through the categorisation task;
2. correlating participants' behavioural patterns (e.g. visual attention, navigation) during the categorisation task in relation to their representational competence;
3. confirming if the identified patterns are specific to the context of representational competence, through the equation-balancing task.

The categorisation task confirmed that our experts were representationally more competent than the novices. Although the two groups did not differ in terms of attention patterns while observing representations during the categorisation task, their navigation (i.e. eye-movement) patterns were considerably different from each other. Further, no such differences were observed during the equation-balancing task, indicating that navigation, and not attention patterns, are the perceptual markers of representational competence.

The Study

We first sought to answer the following two questions to identify perceptual markers of representational competence:

- Question 1: How do participants with different levels of education in chemistry differ in representational competence? (Establishing representational competence-levels/expertise)

- Question 2: What are the behavioural, specifically gaze-related patterns associated with representational competence? (Correlating representational competence with perceptual-sensorimotor markers)

To answer both questions, we adapted Kozma and Russell's (1997) categorisation task (Appendix 1). In their task, Kozma and Russell asked experts (chemists, doctoral students and a community college teacher) and novices (undergraduate students) to sort various representations (equations, dynamic graphs, molecular animations, and laboratory experiment videos; presented as physical cards and computer displays) belonging to different chemical phenomena (Kozma & Russell, 1997; pp. 952-955). Kozma & Russell determined participants' level of representational competence (our Question 1), based on the quality of categories of representations they generated (e.g. extent of application of chemical principles).

Importantly, as this task requires participants to perceptually process and physically interact with representations (Kozma & Russell, 1997; pp. 953), its adaptation provided us the opportunity to observe our participants' perceptual-sensorimotor behaviour (Question 2).

Secondly, we considered the alternate explanation that any behavioural differences seen during categorisation are always present, and are not necessarily markers of representational competence. To test this possibility, we analysed participants' behaviour during an equation-balancing task, that involves stimuli (representations such as equations) structurally (i.e. perceptually) similar to those used in categorisation, but does not necessarily require representational competence (e.g. imagining chemical dynamics) for successful completion (Krajcik, 1991; Yarroch, 1985). In other words, balancing chemical equations is largely based on algorithms.

- Question 3: Are the identified markers always present, or triggered and exhibited only while solving representational competence-related tasks? (Are the identified behavioural patterns representational competence-specific markers?)

Previous studies primarily used this task to probe student conceptual understanding about chemical phenomena in relation to the submicroscopic, particulate and symbolic representations (e.g. by asking high-school students to balance simple unbalanced chemical equations and draw particulate diagrams of the represented chemical reactions; Ben-Zvi, Eylon & Silberstein, 1987; Salta & Tzougraki, 2011; Yarroch, 1985). In the present study, we asked each participant to mentally (i.e. without using pen/paper) balance the given unbalanced chemical equations as we recorded their (gaze) behaviour (Appendix 2).

Our adaptation of the balancing task broadly exploits a well-established experimental paradigm in cognitive psychology – interference (e.g. Stroop, 1935). If the perceptual-sensorimotor changes (e.g. distinct gaze patterns captured during categorisation) among experts were task-general (i.e. not specific to representational competence), they would also be exhibited (i.e. interfere) during a different task involving perceptually similar stimuli (e.g. chemical equations), regardless of whether that task demanded representational competence. If this happens, it will show that simply displaying a representation in a non-representational competence-context would automatically trigger among participants, particularly experts, a mental simulation of the represented chemical process.

Two chemistry experts and one learning sciences expert collectively discussed the usability and validity of the representations used in both tasks, for content, conceptual and representational appropriateness. Their comments and suggestions were incorporated in the final stimulus designs.

Sample

We had the following two broad screening criteria when inviting potential participants for the study: (i) All experts should have some research and teaching experience, and (ii) all novices should be studying chemistry at intermediate level (i.e. neither beginners nor advanced). These were devised to increase the likelihood of obtaining distinct representational competence (and hence, perceptual patterns, if any), and to ensure that all participants were familiar with general chemistry representations.

8 chemistry professors (expert group, 4 females; mean-age = 39.4 years) and 7 undergraduate students (novice group, 4 females; mean-age = 19.5 years) from a leading university in south Asia volunteered to participate in the study. Each expert had at least 5 years of post-PhD teaching and research experience in (general as well as specialised areas of) chemistry. All novices were in the 4^{th} semester of their 6-semester bachelor's diploma in chemistry.

Informed consent, regarding eye-tracking, video recording, and overall participation in the study, was obtained from all the participants.

Procedure

Participants performed the tasks individually. Each participant, on arrival in the lab, sat in front of a laptop screen at 50-70 cm. The laptop was equipped with a Tobii X2-60 portable eye-tracker (Tobii Technology, Sweden). The researcher sat next to the participant and controlled the stimulus presentation using a mouse. Eye-tracker calibration was performed before proceeding to the tasks.

Each participant completed the balancing task first, followed by categorisation, to avoid possible priming effects arising out of exposure to chemistry representations, and/or the act of performing categorisation.

Figure 1 provides schematics of the experiment procedure.

--Figure 1--

First, six unbalanced equations were presented to the participant, one-by-one in a predetermined randomised sequence. The participant was asked to balance each equation mentally. There was no time limit (Appendix 3).

Next, the researcher introduced the participant to the categorisation task. Each participant first viewed nineteen representations (images and movies) on the laptop screen, presented one at a time in a predetermined randomised sequence. On viewing each representation, the participant was given a physical card with a still image of that representation. Once the participant had viewed all the nineteen representations, they were asked to group the corresponding cards into chemically meaningful categories and justify the categorisation scheme. In the original task, Kozma and Russell had allowed participants to go back and forth while viewing the computer displays. To avoid cluttering of the eye-tracking data, we did not allow the participants to shuffle between the displays. Our participants could, however, shuffle between the cards given to them. The participant then performed a second categorisation round/trial using a different grouping scheme. This was to facilitate non-spontaneous, well-thought or alternative schemes, if any (Kozma & Russell, 1997).

During both tasks, a Tobii X2-60 eye-tracker captured fine-grained data on participant's gaze behaviour, and their on-screen activity. The entire experiment was video recorded using a Sony camcorder to capture verbal and gesture data.

Main forms of data were: (a) researcher's notes (e.g. balancing task responses), participants' categories of the representations, (b) video recordings, and (c) gaze-behaviour recordings (e.g. fixation and eye-movement).

In the analysis below, we present frequentist statistics, even though the number of participants in the study is small. Note that this use is descriptive, i.e. to capture the overall structure and pattern of the data. We do not claim statistical significance, although, several results show significant between-group differences.

Performance analysis

Categorisation task. The video recordings and researcher's notes were transcribed, annotated and coded by the first author to analyse the nature of categories generated by participants. Our qualitative coding scheme was informed by Kozma and Russell's (1997) theoretical structures (e.g. phase-based, chemical reaction-based, or media-based sorting; Appendix 4 provides more details and examples of our scheme in comparison to Kozma & Russell). Each category of representations was assigned to one of the following five qualitatively different category-types:

i. Inappropriate or incorrect

ii. Media-based (categorisation based on the medium of representations, e.g. animation, video)

iii. Feature-based (categorisation based on similarities in visual features of representations)

iv. Mixed (categories with correct or plausible combinations of representations, where some associations and/or representations are explained through chemical principles while others through visual features)

v. Conceptual or chemically meaningful (combinations of representations based on chemical principles and supplemented with correct conceptual description)

The first author and an independent blind coder participated in the reliability test. A Cohen's kappa analysis of the two raters' independent ratings involved the above-mentioned category-types and the categorisation data of 3 experts and 3 novices. On analysis, both coders were found to have 100% agreement ($k = 1$).

The following data were tabulated for each participant per categorisation trial: Total cards used, total categories generated, and number of categories of each type. For each participant, the 'best of two' trials (as indicated by the mean number of conceptual and mixed categories, in contrast to media-based or feature-based categories) was considered for group level analysis.

In addition, participants' gestures and actions during the task (e.g. through video transcripts) were analysed for potential qualitative between-group differences. Screen recordings also provided viewing duration for each representation.

Balancing task. Accuracy/performance results were ignored as this was a confirmation task examining only gaze patterns.

Gaze-data analysis

We were interested in two important types of potential perceptual markers of representational competence: (a) attention-related, and (b) navigation-related (Cook et al., 2008; Gegenfurtner et al., 2011; Kohl & Finkelstein, 2008; Stieff et al., 2011). However, unlike previous eye-tracking studies, we will interpret gaze behavioural results through an action-based (extended and embodied) lens as elaborated in the theoretical background.

Categorisation task. Tobii Studio 3.2 (Tobii Technology, 2014) was used to analyse gaze data. Participants' viewing duration and saccade frequency were determined for each representation.

Different non-overlapping Areas of Interest (AOIs) were then defined for each representation. Here, we report data related to graphs and equations (static representations) only. Gaze-data analysis for animations and demonstration videos (i.e. dynamic representations) was excluded to avoid complexity arising as a result of constantly changing stimulus frames and consequent gaze behaviour. Further, equation-related gaze data had a special value (as a point of comparison with data from the equation-balancing task) in confirming the representational competence-related specificity of sensorimotor behaviour (Question 3).

Figure 2 indicates the AOIs generated for graphs (2a) and equations (2b).

--Figure 2--

The following metrics were calculated per AOI per set of representations (i.e. set of all equations, set of all animations, and so on), for each participant: Viewing duration, fixation count, and fixation duration (Appendix 5). These attention-related data were then subjected to descriptive statistical analysis.

Further, to examine how the two groups visually navigated each set of static representations, gaze-transitions between the AOIs were generated for each participant. Gaze transition is an eye-movement between any two successive eye-fixations that occur in two different AOIs. Note that gaze transitions are not the same as saccades; non-AOI fixations are ignored while calculating transitions (Appendix 5).

For graphs, we discuss these AOI-based data using transition diagrams.

Unlike some of the previous eye-tracking studies (e.g. Cook et al., 2008; Kohl & Finkelstein, 2008), we were also interested in the quality of transitions and not merely in their frequency. For chemical equations, we will identify two (qualitatively different) types of transitions: long and short transitions (figure 3) The words 'short' and 'long' refer more to the conceptual relation between the AOIs (than a spatial one).

--Figure 3--

Transition data were used to calculate the following two unique indicators of overall gaze activity per representation:

- Inertia = $\dfrac{\text{number of transitions made to the same AOI}}{\text{total number of transitions}}$

- Volatility = 1 – inertia

Inertia indicates how flexible a participant is in exploring novel relationships between AOIs. Volatility indicates how fixated a participant is over one or few AOIs.

Between-group differences in transition frequency and volatility were analysed, and the nature of transitions was interpreted through graphical visualisation. These would be the navigation-related markers of representational competence.

Balancing task. The gaze data analysis was similar to that used for the categorisation task data.

Desired results

1. **Experts will have higher representational competence than novices (Question 1)**: We anticipated our experts to make more chemically meaningful (i.e. either conceptual or mixed) categories as compared to novices (Chi et al., 1981; Kozma & Russell, 1997). Further, following from the perceptual learning theory, we expected lower viewing duration for each representation for experts than novices.
2. Experts' will exhibit distinct *attention* patterns from novices (Question 2): We anticipated the experts to exhibit lower fixation counts, and fixation duration across the different AOIs of each representation than the novices, as a result of experts' longer experience with the representations as well as represented phenomena (Chen et al., 2014).
3. Experts will show distinct *navigation* patterns from novices (Question 2): We anticipated (a) novices to exhibit either lower or higher saccade frequency while navigating each representation than experts (Gegenfurtner et al., 2011). Lower, because novices may make more attempts to understand components (AOIs) of a representation than to figure out the relationships between them. In contrast, higher frequency of saccades would indicate novices' increased attempts to find relationships between those components. (b) Similar patterns to (a) for transitions, and transition type (e.g. short and long). (c) Similar patterns to (a) and (b) for volatility values; lower volatility among novices would indicate that the novices may 'see' only limited relations between representations and their components, while higher values would mean that they are desperately looking for relations all over the representation (Cook, 2006).

4. The identified perceptual-sensorimotor (i.e. attention and navigation-related) patterns are specific to representational competence and expertise (Question 3): We anticipated the two groups to exhibit similar gaze-behaviour patterns (e.g. transitions, volatility) in the balancing task.

Results similar to these expectations would provide evidence in favour of our broader theoretical conjecture – experts' perceptual-sensorimotor system is tuned over the years during the development of representational competence, as a result of their interaction with representations.

Results

Establishing differences in representational competence-levels (Question 1; desired result 1)

Table 1 shows the category distribution for experts and novices across the pre-defined five types of categories (best of two trials).

--Table 1--

Experts clearly made more conceptual and mixed categories than novices. They also relied less on visual features of the representations than novices, who made comparatively more feature-based categories. The two groups did not differ in the number of media-based categories; both made very few of these on average. Every novice made nearly one incorrect or inappropriate combination of representations per trial on average, while none of the experts provided any inappropriate or incorrect justifications.

Consistent with results from previous studies (e.g. Kohl & Finkelstein, 2008), novices viewed each representation for longer than experts on average (table 2).

--Table 2--

Two experts began categorisation by first arranging the representations medium-wise, and then proceeded to relate them more conceptually; figure 4 shows such an instance.

--Figure 4--

A few other experts found it useful to initially spread the representations on the table, to obtain an overview. None of the novices performed any such action to gain an overview of the representations. All the novices either held all the representations together in their hands, or put stacks of them on the table, only to view/handle one or a pair of representations at a time.

Overall, results from the categorisation task confirmed that our experts were representationally more competent than novices across the reported quantitative and qualitative measures.

Perceptual markers of expertise (Question 2)

Having established the expert-novice status (i.e. representational competence), we now discuss representational competence-related gaze patterns across several parameters.

Attention patterns (desired result 2). Table 3 presents the distribution of fixation count and duration across the different AOIs in equations and graphs. The quantities have been normalised[3] for viewing duration for respective representation for each participant; remember that experts and novices exhibited different viewing durations.

--Table 3--

Overall, the two groups did not differ from each other in gaze-spread over the different elements in equations and graphs. Unlike our expectation, we found no indicative between-group

[3]For the purpose of our analysis, we present certain frequencies per 10 seconds relative to the (viewing duration), instead of per second, as the latter values appeared to be too small in their magnitude to discuss meaningfully.

differences in attention patterns – experts' familiarity with the representations thus had no effect on their attention behaviour.

Navigation patterns (desired results 3a, 3b & 3c). Because of their longer viewing duration, novices recorded more saccades for each representation than experts. However, in contrast to our expectation in 3a, the two groups did not differ from each other in saccade frequency per unit viewing duration (table 4).

--Table 4--

From the transition data, we found that our experts and novices did not differ in total between-AOI transitions across graphs (experts = 662, novices = 541), or equations (experts = 323, novices = 258). However, the two groups differed in transition frequency per unit viewing duration both on graphs (experts = 10.01 transitions/10seconds, SD = 2.92; novices = 5.76/10seconds, SD = 2.72; $p = .05$), and equations (experts = 11.61/10seconds, SD = 5.34; novices = 5.63/10seconds, SD = 4.55; $p = .02$). This result matches our expectation 3b.

We will now discuss an AOI-specific analysis of the quality of transitions for graphical representations. Later, we will discuss the same for equation representations.

Figure 5 shows a normalised distribution of transitions for experts and novices between the different AOIs for all the graphs combined.

--Figure 5--

As anticipated in 3b, experts transited more frequently between curve and Y-axis (44.78% transitions) by a considerable margin as compared to between curve and X-axis (31%). Novices showed a nearly opposite pattern (35.45% and 44.26% respectively). Coincidentally, X-axis in each graph showed the independent variable, whereas Y-axis depicted the dependent variable. Given that the dependent variable indicates properties of a reaction system, we speculate that our experts were interested in deriving meaning from how the dependent variable is responding to the independent variable (process dynamics), while the novices may have been trying to figure out what would the response (value) be. However, none of the experts' transcripts corroborated this speculation.

Experts' gaze-transitions had a balanced mix of long and short transitions, but considerably larger proportion of long transitions (experts-mean = 48.92%, SD = 4.23) than novices (novices-mean = 30.62%, SD = 2.58) at $p < .01$. Inversely, they performed very few short transitions as compared to the novices.

In terms of volatility (indicator of how flexible a participant is in moving their eyes), the two groups did not differ across graphs much (experts-mean = 0.38, SD = 0.05; novices-mean = 0.33, SD = 0.06). However, across equations, novices showed lower mean volatility index of 0.25 (SD = 0.09) than experts (mean = 0.33, SD = 0.05) at $p < .05$. Experts thus were almost 1.5 times more flexible in exploring the different AOIs in equations (expectation 3c).

Overall, the obtained results matched our expectations (except 3a).

Confirming gaze-behaviour specificity (Question 3, desired result 4)

Having found no between-group differences across fixation parameters in the categorisation task (i.e. representational competence-related task), we do not discuss results for those parameters in relation to the balancing task, as our aim is to confirm the specificity of perceptual patterns identified thus far to representational competence. For similar reasons, between-task differences are reported elsewhere (Author, 2018).

As expected, the two groups did not differ in any of the navigation-related parameters: Saccade frequency/10seconds (experts-mean = 48.57, SD = 8.91; novices-mean = 44.30, SD = 13.89); total transition frequency (experts-mean = 316.06, SD = 311.17; novices-mean = 440.88, SD = 392.84); transitions/10seconds (experts-mean = 19.38, SD = 11.59; novices-mean = 19.01, SD = 11.43). Further, there was no difference in the quality of transitions between the different equation AOIs; on average, 26.82% transitions for experts were long transitions (SD = 5.49), while the proportion for novices was 26.4% (SD = 6.64).

Finally, experts did not vary in volatility values in the balancing task (0.47; SD = 0.09) from novices (0.41; SD = 0.05).

Summary and discussion

The representational competence-related results confirmed that the professional chemists and teachers we recruited as experts were indeed representationally more competent than our novices (undergraduate students). In terms of perceptual-sensorimotor differences, as table 5 summarises below, experts' attention patterns were no different from novices. However, experts did differ from novices in the way they navigated representations during categorisation (e.g. qualitative physical handling of the cards/representations, eye-movement), suggesting a relationship between representational competence and perceptual navigation patterns.

--Table 5--

Further, as anticipated, presenting perceptually similar representations (equations) in a non-representational competence-context did not trigger such distinct perceptual navigation behaviour among experts. This confirmed that experts' distinct perceptual markers are exhibited only when the cognitive system recruits representational competence. If the sensorimotor (perceptual navigation or eye-movement-related) changes among experts were task-general (i.e.

not specific to representational competence), they would be exhibited regardless of whether a task exploited representational competence, whenever perceptually similar stimuli (e.g. chemical equations) were presented to them. This result indicates a role of context in sensorimotor simulation, as other studies show that the perception of a stimulus automatically triggers the simulation of one's interaction with that stimulus (Barsalou, 2008; Chandrasekharan, 2009).

Perceptual navigation patterns indicate participants' attempts to integrate different parts of a representation (Holsanova, 2014), unlike attention, which is a measure of how much emphasis a participant gives to certain parts of that representation. Eye-movements are also related to the binding between one's internal representations and external representations into a coherent integrated mental model (Gilbert, 2005; Levy & Wilensky, 2009). However, our results suggest that the relation between expertise and different measures of eye-movement is more complex. For instance, a high frequency of saccades may not necessarily mean that a participant's coordination between features of the representations was systematic, as in the case of our novices, who made fewer, and qualitatively inferior, between-AOI eye-movements while viewing equations and graphs, despite exhibiting high saccade frequency and representation viewing duration (Cook et al., 2008; Kohl & Finkelstein, 2008). Experts exhibited exactly opposite patterns, indicating that their eye-movements were more efficient in binding of the kind mentioned above.

Indicative evidence from our pilot studies in the past has shown that this expert-novice difference in perceptual navigation could be a function of growing expertise. Undergraduate students who performed categorisation in ways similar to experts (Authors, 2015), in one such study, tended to exhibit expert-like gaze patterns across equations and graphs, in contrast to relatively novice candidates who scanned equations linearly with long pauses in between, with nearly twice as many short transitions as long transitions (figure 7).

--Figure 7--

Previous research in the broad domains of learning and instruction has demonstrated that providing gaze-based cues on stimuli presented during problem solving in a learning interface helps participants gain insights into problem solutions (Litchfield & Ball, 2011; Jarodzka et al., 2013). These cues – static or dynamic replays of specific fixation and/or eye-movement patterns – are often modelled on experts' gaze patterns. Eye-movements are rapid and spontaneous during navigation (e.g. in space, through stimuli), and are considered automatic and implicit (i.e. not completely in one's control, Irwin, 2004). These instructional approaches based on gaze cues (implicitly or explicitly) exploit the effect (of the kind our study demonstrates) that instruction and/or knowledge have on one's perceptual-sensorimotor behaviour (Kostons et al., 2009). This effect, often dubbed as experts' 'visual strategies', is difficult to explain through an information processing stance, which considers representations to be mere carriers of information, and the eye as an extractor of information (Klein et al., 2018; Madsen et al., 2012). Following from the recent enaction-based models of expertise (Authors, 2017; Braithwaite et al., 2016) we interpret this change in experts' behaviour as a systematic fine-tuning of their perceptual-sensorimotor system, emerging from their interaction experience with representations and conceptual systems (Author, 2020).

Further corroborative evidence in this direction is provided by the fact that our experts employed assumedly 'irrational' actions, from a solution point-of-view, such as spreading the cards/representations on the table and devising preliminary criteria to arrange them on the table, before proceeding to form finer categories (e.g. expert2, figure 4). Experts in various domains are known to perform such systematic actions – termed ‘epistemic actions’ (Kirsh & Maglio, 1994) during tasks, in order to change structures in their environment to optimise search for a solution and/or lower the cognitive load generated in a situation (Kirsh, 2010). But most importantly, epistemic actions help experts see newer relationships between the task elements and representations (Aurigemma et al., 2013; Kirsh & Maglio, 1994). Epistemic actions are different from ‘pragmatic actions’, in that the latter only bring the agent physically closer to a goal, without serving any specific cognitive role. The actions some of our experts performed cannot be considered pragmatic given their cognitive role in helping the experts gain newer insights into relationships between the representations, which were initially not imagined, or only partially imagined. These relationships, which the experts used to form finer categories, ‘appeared’ to the experts only after performing an epistemic action (e.g. sorting the representations media-wise). This is also consistent with new behavioural evidences from research on action-based learning (e.g. Goldin-Meadow, 2011; Kang, Tversky & Black, 2015), and learning through interactive computer-supported environments (e.g. Basu, Sengupta & Biswas, 2015; Kothiyal et al., 2014; Majumdar et al., 2014; Virk & Clark, 2019). These new evidences demonstrate how one’s richness of understanding of concepts and representations in science (i.e. expertise) is related to their overall interaction behaviour, besides gaze (e.g. frequencies and patterns of mouse-clicks, drags, gestures).

The 'sensorimotor fine-tuning' approach may also help explain how some experts (e.g. chemists) make seemingly mysterious ‘micro’ and instantaneous decisions (and actions) during practice (e.g. while carrying out chemical processes such as synthesis). Most such instances are reported as anecdotes of ‘intuition’, with limited understanding of how these intuitions are acquired during learning (Kutchukian et al., 2012).

While the education and learning sciences communities broadly agree that even seemingly abstract learning is grounded in body-based interaction between the learner and the world (Barsalou, 2008; Landy et al., 2014), and that learners’ qualitative and ‘pre-symbolic’ understanding and interactions with the world evolve into their sophisticated formulations (Abrahamson, 2019; Abrahamson & Sánchez-García, 2016; Markauskaite et al., 2020; Nemirovsky & Ferrara, 2020), it is debated whether experts' distinct sensorimotor behaviour manifests expertise or is a manifestation of expertise. It would also be interesting to explore if different kinds of expertise (e.g. scientific, or pedagogical or both) and/or experience within a broad scientific domain exhibit different sensorimotor behaviours (Pande & Sevian, 2016).

More research is needed to understand if, when, and how distinct perceptual-sensorimotor behaviours evolve with the development of representational competence and expertise in science. Gaining insights into this relationship is critical to understanding the process of learning, clarifying the nature of expertise, and designing effective learning interventions.

Conclusion

We report a theoretically motivated investigation of sensorimotor markers of representational competence and expertise in the context of chemistry. Our results extend findings from previous research, indicating that distinct perceptual *navigation* (eye-movement) marks expertise in chemistry. Further, we show how this marker is triggered specifically while solving problems that demand representational competence, and how this could be related to the growth of expertise (Authors, 2015). The specific activation of experts’ perceptual-sensorimotor behaviour indicates that their perceptual system could be 'tuned' to support representational competence, allowing them to seamlessly integrate perception and imagination processes, as well as (epistemic) actions. These findings support ‘field’ models of science cognition, and open up new avenues for research in science education, and learning and educational technology design. However, we consider these results as only indicative, because our sample size was limited. Future approaches to studying the co-development of domain expertise and perceptual-sensorimotor tuning, based on interaction with representations, would need to simultaneously investigate the embodied-cognitive as well as the situated-social mechanisms supporting representational competence (Kozma, 2020). These approaches may demand an employment of wider cross-sectional and/or longitudinal methods in more situated/ecological research settings, to investigate questions such as when and how stable perceptual-sensorimotor behaviour is exhibited in the development process, and how findings related to these questions can inform new designs for science learning.

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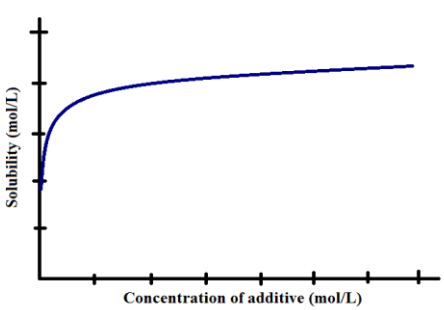
Appendices (supplementary material)

Appendix 1

For the categorisation task, we chose five different chemical reactions from different undergraduate general chemistry textbooks: a strong acid-strong base neutralisation reaction, a precipitation reaction, NO_2-N_2O_4 gas equilibrium, and two other equilibrium reactions involving complex-ions. For each reaction, we generated the following external representations with the help of a professional 3D animator using image processing and animation software: a chemical equation and a graph (static representations), a laboratory demonstration of the reaction and a 3D molecular animation (space-fill models) depicting the overall molecular dynamics (e.g. particulate collision; dynamic representations). All the representations were unannotated (e.g. the dynamic representations did not embed textual information or any other representation).

An image or screenshot of each representation was colour printed on a cardboard for hands-on categorisation.

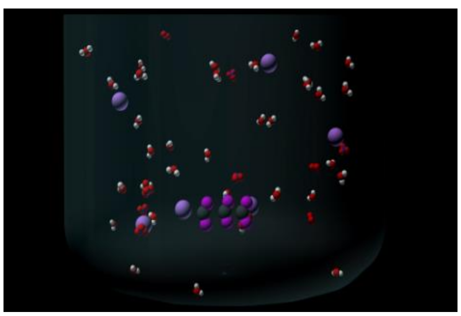
Sample representations used in the categorisation task (screenshots)

Image	Description of the representation
	A solubility vs. concentration curve governing the dissolution of silver chloride in relation to the concentration of ammonia.

$$NaOH_{(aq)} + HCl_{(aq)} \Downarrow NaCl_{(aq)} + H_2O_{(l)}$$

Representative equation of a neutralisation reaction between strong base and strong acid.

Demonstration video of the precipitation reaction between potassium iodide and lead nitrate.



3D molecular animation depicting the dynamics of the above reaction.

Appendix 2

The stimuli were six different chemical equations from a general chemistry undergraduate textbook, with randomly deleted coefficients, subscripts and superscripts from the reactants and products in those equations; thus generating images of unbalanced equations.

Sample chemical equation-balancing problem:

Image

$$Al(OH)_3 + H_3O^+_{(aq)} \rightleftharpoons Al^{3+} + H_2O$$

Appendix 3

Instructions given to each participant during the Balancing task:

You will be seeing a simple unbalanced chemical equation and your task is to balance it. No paper and pencil are available as you are expected to do it mentally. There is no time limit, so you can take as long as you want. You can also proceed to the next equation if you find the current one difficult but remember that you will not be allowed to return to the equation you skip.

Instructions for the categorisation task:

Now we begin the second task. Here, I will be showing you one by one, a number of representations such as chemical equations, graphs, 3D animations and laboratory demonstration videos on the laptop screen. When I show you each representation, I will be handing over to you a card with the corresponding representation printed on it. In case of animations and demonstration videos, the card will have a screenshot of some moment in the movie. Attend to each representation on the screen carefully as you will not be allowed to return to it after you have proceeded to the next one. You can take as much time as you want to view each image, and watch each movie as many times as you want before proceeding to the next. Once you have seen all the representations on the laptop and collected all the corresponding cards with you, I will tell you what to do with them.

On completion of the experiment, the participant was informed to not discuss any details about the study with their peers.

Appendix 4

Category coding scheme (informed by Kozma & Russell, 1997).

Nature of categories	Criteria	Example	Kozma & Russell (1997) equivalent
Conceptual	Chemically meaningful combinations of cards, supplemented with correct conceptual description of chemical principles (e.g. phase-based, chemical reaction-based)	Associations of cards depicting equilibrium reactions	This type of categories is comparable to Kozma & Russell's 'conceptual sorts' (pp. 957, paragraph 6, lines 1-2; description and examples continued to page 958).
Mixed	Categories with correct or plausible combinations of cards, where some associations and/or representations are explained through chemical principles while others through visual features	A category made with 4 cards depicting equilibrium reaction; of which, two cards are explained using the concept of equilibrium, while the other two using feature-similarity such as Δ (heat symbol) and a burner.	This type of categories is comparable to Kozma & Russell's 'partial sorts' (pp. 956, lines 13 onward; continued to page 957).
Feature-based	Associations of cards explained purely through visual features of the representations	Associating an animation showing molecules settling down with a laboratory demonstration of precipitation; explained in words such as, 'both settling down'.	Surface-feature-based (pp. 957, paragraph 6, lines 3 onward; description and examples continued to page 958)
Media-based	Combinations of cards based on the medium of representation	All molecular animations as a category, all graphs as another, and so on.	Komza & Russell refer to this as 'perfect media' sorts (pp. 956, paragraph 2).
Inappropriate or incorrect	Incorrect combinations of cards	An association between equation of a precipitation reaction and a video showing effect of temperature on a chemical equilibrium	No Kozma & Russell equivalent. Their sorting results did not appear to have any completely incorrectly made categories. Perhaps many sorts made by their sample were only partially incorrect, hence included in the 'partial' sorts.

Appendix 5

Definitions of gaze parameters.

Fixation point	Point (location) on the stimulus where the eye is fixated.
Fixation index	Represents the order in which a fixation event was recorded. The index is an auto-increment number starting with 1 (first gaze event detected).
Fixation duration	The duration of each individual fixation for a participant within an AOI.
Fixation count	This metric measures the number of times the participant fixates on an AOI or an AOI group.
Saccade	Movement of the eye between fixation points.
Gaze Transitions	Eye movements between two consecutive fixations (e. g. A-B, where A and B are two different AOIs) Gaze transitions are systematic eye-movements between fixations. The nature of gaze transitions is considered an important marker of a participant's activity of comparing between and integrating multiple AOIs, and the content they embed. For our analysis, a transition Saccades are the eye movements between two consecutive fixations, irrespective of AOIs. Transitions, however, are those saccades between consecutive fixations happening between two different AOIs. Consider two AOIs *x* and *y*, for instance*;* now suppose if the first few fixations happen in *x* and the next fixation(s) happen in *y*, our algorithm would register only one transition between *x* and *y*. However, the eye-tracker will register many saccades between the fixations irrespective of *x* and *y*. Hence, all transitions are saccades, but all saccades are not transitions.
Inertia	The number of transitions made to the same AOI/total number of transitions. Inertia indicates how flexible or rigid a participant is in terms of visiting different parts of a representation. Alternatively, it could also be understood to indicated how stable a participant is in navigating the different parts of a representation.
Volatility	1 – inertia.

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Figures

--Figure 1--

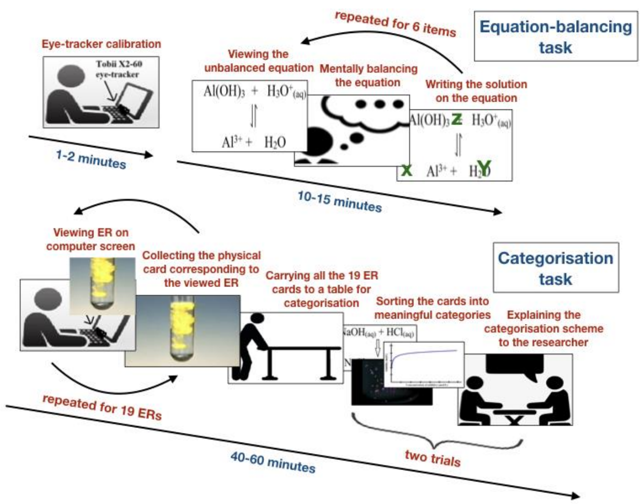

Figure 1. Experiment setup and protocol (ER = external representation).

--Figure 2--

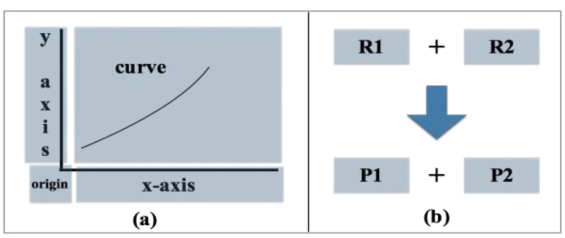

Figure 2. AOIs for (a) graph representations, (b) chemical equations. Each shaded box is a separate AOI (R = reactant, P = product). AOI shapes and sizes may differ for each representation.

--Figure 3--

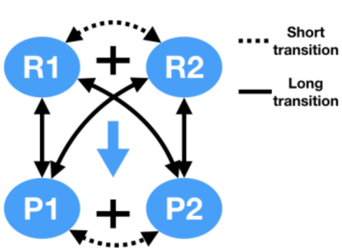

Figure 3. Long and short transitions between AOIs of a chemical equation (R = reactant, P = product). Arrows indicate direction of transitions.

--Figure 4--

Figure 4. An episode of ‘epistemic’ actions (Kirsh, 2010) – in (1), expert2 is seen sorting the representations media-wise and keeping them on the table as four different stacks. In (2) she picks up two representations from the stack of chemical equations and compares them, while the other three sets of representations (animations, video-snapshots and graphs) lie on the table. In (3), the participant has spread all the equations – another epistemic action performed to improve perceptual reach. She is also comparing the graphs (held one in each hand) either with each other or the equations. In (4 and 5), expert2 can be seen comparing different representations and placing them together. Finally, (6) depicts the completion of expert2’s categorisation.

--Figure 5--

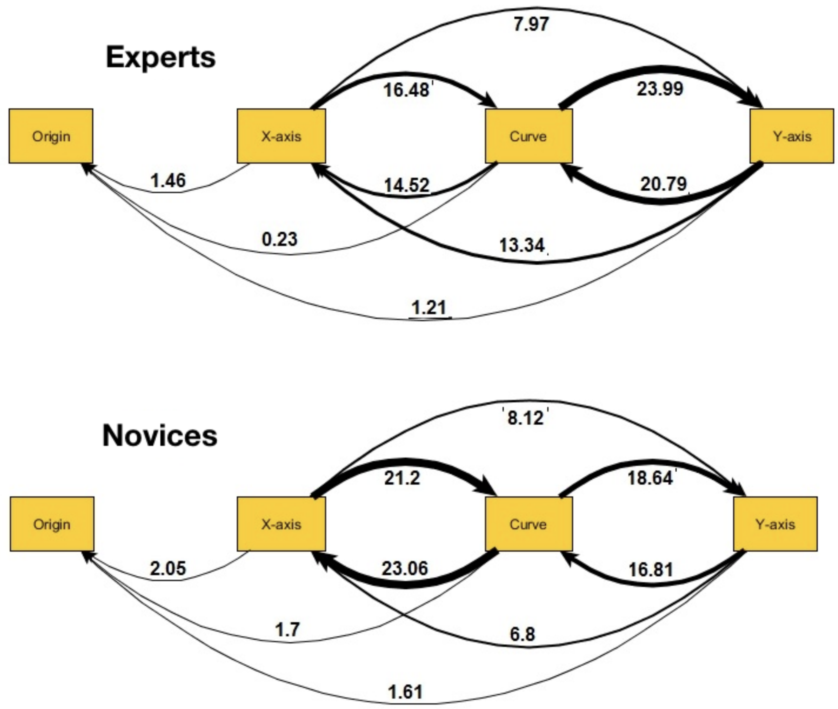

Figure 5. Percent transitions between AOIs averaged across all graphs. Each box represents an AOI. Direction of the arrow indicates direction of the transition. The thickness and the numbers on the arrows indicate the relative number of transitions between those two AOIs. The transition patterns of experts are qualitatively different from those of the novices.

--Figure 6--

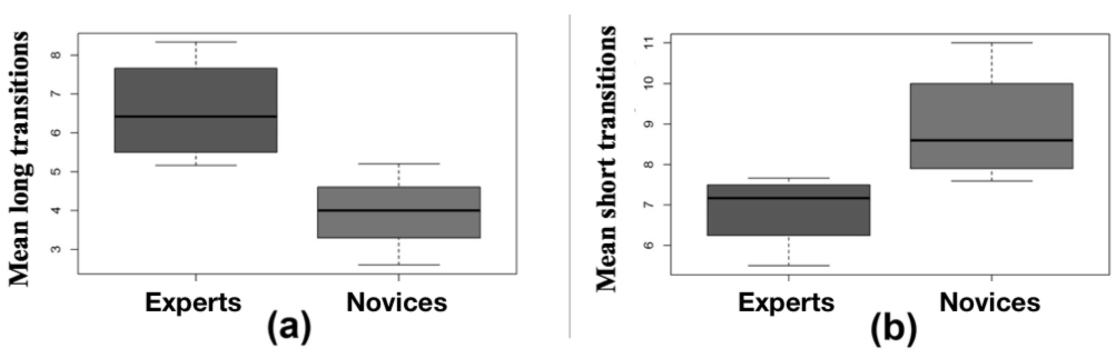

Figure 6. Box plots depicting (a) mean long transitions ($p < .001$); and (b) short transitions for experts and novices ($p < .01$) across equations.

--Figure 7--

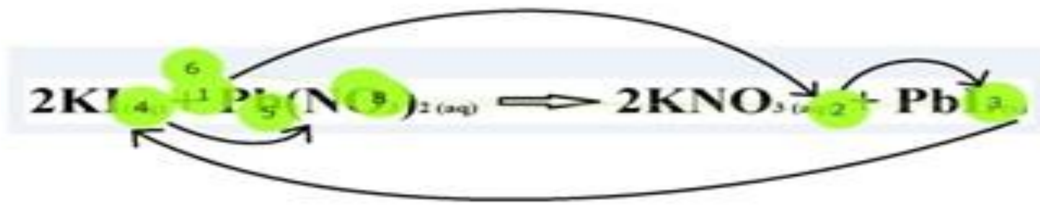

Figure 7. An instance of gaze behaviour of an expert-like undergraduate student (Authors, 2015). Arrows indicate direction of transitions. This student makes fewer but focussed fixations and equally frequent short and long transitions.

Tables

--Table 1--

Nature of categories (best of two rounds/trials)

Nature of category	**Experts**	**Novices**	***p-value***
Conceptual	1.5 (1.19)	0.28 (0.49)	.05*
Mixed	1.83 (0.65)	0.71 (0.76)	.01*
Feature-based	1.16 (0.83)	3.29 (1.38)	.00*
Media-based	0.67 (1.07)	0.57 (0.53)	.46
Inappropriate	0 (0)	0.85 (1.07)	.18

Mann-Whitney U-test for independent samples

--Table 2--

Mean viewing duration in seconds

	Experts	**Novices**	***p-value***
Equations	13.65 (8.45)	26.94 (21.84)	.00*
Graphs	21.43 (12.44)	35.25 (24.06)	.00*
Animations	38.75 (26.34)	69.65 (31.76)	.01*
Demonstrations	64.98 (38.18)	125.28 (73.11)	.00*

Mann-Whitney U-test for independent samples

--Table 3--

Fixation count and fixation duration per 10 seconds (R = reactant, P = product)

Fixation count/10sec

	Equations					**Graphs**			
AOIs	**Arrow**	**R1**	**R2**	**P1**	**P2**	**Origin**	**Curve**	**X-Axis**	**Y-Axis**
Experts	0.45	8.19	2.70	10.74	8.25	0.30	7.74	4.46	6.26
	(0.82)	(13.54)	(3.04)	(14.32)	(14.01)	(0.68)	(6.05)	(4.04)	(4.69)
Novices	0.75	5.63	5.42	5.36	1.70	0.38	8.31	8.50	4.18

	(1.06)	(4.78)	(3.45)	(4.63)	(1.40)	(0.81)	(5.62)	(9.34)	(3.47)
p	.09	.63	.42	.39	.34	.64	.59	.06	.11

Fixation duration/10sec

	Equations					**Graphs**			
Experts	0.04	1.11	0.77	0.76	0.35	0.03	1.24	0.64	1.11
	(0.11)	(1.02)	(0.72)	(0.85)	(0.47)	(0.08)	(1.10)	(0.65)	(1.03)
Novices	0.11	0.98	0.93	0.92	0.32	0.07	1.48	0.83	0.75
	(0.16)	(0.88)	(0.72)	(0.89)	(0.28)	(0.16)	(1.21)	(0.68)	(0.70)
p-value	.03*	.88	.29	.24	.59	.50	.41	.13	.31

Mann-Whitney U-test for independent samples

--Table 4--

Mean saccades per 10 seconds for each type of representation

Mean saccades/10 seconds	**Experts**	**Novices**	***p-value***
Equations	1.21 (0.90)	1.40 (1.15)	.55
Graphs	1.46 (1.07)	1.65 (1.10)	.29
Animations	0.35 (0.22)	0.32 (0.17)	.88
Demonstrations	1.11 (0.79)	1.45 (0.93)	.13

Mann-Whitney U-test for independent samples

--Table 5--

Task-specific differences between experts and novices across parameters of attention and navigation

Between-group differences in tasks across behavioural parameters		**Measures of attention**			**Measures of navigation**		
		Saccades	**Fixation count**	**Fixation duration**	**Transitions adjusted to viewing duration**	**Quality of transitions (long & short)**	**Overall quality of navigation (inertia/volatility)**
Categorisation	Graphs	No	No	No	Yes	Yes	No

(representational competence-related task)	Equations	No	No	No	Yes	Yes	Yes
Balancing (non-representational competence task)	Equations	NA	NA	NA	No	No	No

Dear Dr. King,

We thank you and the reviewers for the encouraging comments on the second revision of our manuscript. We have now revised the manuscript to address Reviewer 7's concerns, particularly the concern about *RISE* publications, which was an unfortunate omission on our part. The main changes are below:

- We have provided further clarity on participants' background, in the 'Sample' subsection.
- We have incorporated references to highly relevant *RISE* papers published recently.

In the section below, we provide a more detailed response to the reviewer comments, to further address the issues raised. Our responses are in *Italics.*

We hope you find this revised version acceptable for publication.

Looking forward to hearing from you soon.

Authors

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Responses to reviewer comments

Reviewer 6

Thank you for submitting your manuscript entitled "Expertise as Sensorimotor Tuning: Perceptual Navigation Patterns Mark Representational Competence in Science." This is a very well written paper and a pleasure to read. I found the topic highly relevant for science educators seeking to understand cognition in learning science. The connectivity with embodied cognition is interesting and opens a pathway for the study to connect with both representational cognitive processes and non-representational embodied cognitive performances within authentic learning environments.

> *Thank you for these encouraging comments. We are happy to know that you found our contribution relevant and interesting.*

Reviewer 7

Thank you for the opportunity to read this very interesting and relevant work. I would like to commend you on this research and for writing a very complex study with clarity and within the word limit! I am happy with your response to previous reviewer's comments. It is evident that you have significantly transformed the manuscript by attending carefully to their excellent reviews.

Thank you for these encouraging comments. We are happy to know that our responses to the previous reviews are satisfactory.

I have some minor concerns. Your experts are chemistry professors and your novices are undergraduate chemistry students. There needs to be some clarification of your choice of expert and novice. Chemistry spans many diverse areas – so are these experts in diverse areas or one particular area of chemistry? Why did you choose these experts? Does it matter in relation to the tasks? Some clarity here is important to the findings. Also what about the novices? Why did you choose from this cohort? (4th semester of their 6-semester bachelor's diploma in chemistry). Was this a purposeful or random sample? These questions have ethical consideration as well.

To clarify the details of the sample better, we have added a paragraph on pp. 11 (lines 2-7).

The sampling was done on a voluntary basis (pp. 11, lines 8-10). It was thus a case of availability sampling. Similar to Kozma and Russell's original study, our selection of participants did not assume any specific experiences with external representations in chemistry. However, as also clarified in response to an earlier review, we did have two broad screening criteria, to 1) increase the likelihood of obtaining distinct representational competence profiles (and thus, perceptual patterns, if any), and 2) to ensure that all participants were familiar with general chemistry representations. These criteria were: (i) The expert participants were expected to have some experience in researching and teaching chemistry – as in the original study. Similarly, (ii) the novice participants were expected to be studying general chemistry at an intermediate level; in *principle, students at this stage are familiar with external representations in general chemistry (chemical equations, graphs, molecular animations), such as those used in this study (although, we did not test for this factor/prior knowledge explicitly).*

Both Kozma & Russell's study and our study used participants' educational level, and professional and pedagogical experience with general chemistry (external representations), as a baseline. However, we considered it problematic to assume that: (i) our experts, just by virtue of their educational experience, possessed high RC, and (ii) our novices, because they had limited education and experience in chemistry, had low RC. Moreover, as your query pointed out, our experts specialised in diverse areas of chemistry. Considering these factors, it was important to <u>*confirm*</u> *our participants' expertise (or novice-hood) with general chemistry external representations (question 1; pp. 8), and only then proceed to identifying perceptual-sensorimotor markers (questions 2 & 3; pp. 9-10).*

To address the ethical concerns, the study was conducted according to the Declaration of Helsinki, and informed written consent (e.g. regarding eye-tracking, video recording) was obtained from each participant prior to the study (pp. 11, lines 13-14).

My second concern relates to the appropriate choice of journal for publication. I note that your reference list does not include a single publication from RISE, and yet there are considerable studies around representational competence in RISE. If this work does not connect suitably with the vast array of RISE publications in this area, perhaps RISE is not the right choice of journal for your publication? By extension to this, one could argue that your work may not be suitable for our readership.

Thank you for bringing this omission to our notice. We are aware that RISE has published a vast array of literature on representational competence, and on learning with external models/representations (e.g. Hand, Hubber, Markauskaite, Nichols, Nitz, Prain, Tsui, Treagust, Tytler, Yore, Waldrip, Wu to name a few – some of their other publications have been cited in the present manuscript, as well as our prior and upcoming publications). This makes our research extremely relevant to the RISE readership, thus justifying our choice of the journal.

However, your comment has made us aware that our selection of citations did not include RISE publications. This was an unfortunate omission on our part. We agree with you that connecting the paper to existing work published in RISE is critical to situating our research in relation to the journal's readership. To address this issue, we have revisited our literature citations, to add RISE publications, specifically in relation to perceptual, sensorimotor and cognitive analyses of learning with external models/representations. We have found a few recent papers on this area, which are now incorporated in the manuscript (e.g. pp. 4, line 18; pp. 25, lines 14-15; pp. 26, line 5).

Apart from these citations, which are related to the core claim of the paper, we have also added a few RISE publications in our background literature review (pp. 2, line 13; pp. 5, line 15; pp. 10, line 8).

We hope these responses satisfactorily address the concerns you have raised. We hope to hear from you soon.